Adding Velocity to BigBench
[Work-in-Progress]

Todor Ivanov
(todor@dbis.cs.uni-frankfurt.de),
Patrick Bedué, Roberto V. Zicari
Frankfurt Big Data Lab,
Goethe University Frankfurt,
Germany

Ahmad Ghazal
Futurewei Technologies Inc.
Santa Clara, CA, USA
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BigBench [Ghazal et al. 2013] (presented @SIGMOD 2013)

- End-to-end, technology agnostic, application-level Big Data benchmark.
  - On top of TPC-DS (decision support on retail business)
  - Adding semi-structured and unstructured data.
  - **Focus on**: Parallel DBMS and MR engines (Hadoop, etc.).
  - **Workload**: 30 queries
    - Based on big data retail analytics research
    - 11 queries from TPC-DS
BigBench V2 [Ghazal et al. 2017] (presented @ ICDE 2017)

- BigBench V2 - a major rework of BigBench
  - Separate from TPC-DS and takes care of *late binding*.
- New simplified data model and late binding requirements.
  - Custom made scale factor-based data generator for all components.

### Workload:
- All 11 TPC-DS queries are replaced with new queries in BigBench V2.
- New queries with similar business questions - *focus on analytics on the semi-structured web-logs*.
Motivation

● Growing number of *industry scenarios* requiring streaming and *new streaming engines*:

  - [STORM](#), [Spark Streaming](#), [Flink](#), [samza](#)

● New functionalities combining analytical with streaming features
  ○ Spark Structured Streaming
  ○ Calcite adapted by Flink SQL, Samza SQL, Drill, etc.
  ○ Kafka Streaming SQL - KSQL

● Need of standardized end-to-end application benchmarks covering all Big Data characteristics including velocity:
  ○ *micro-benchmarks*: StreamBench, HiBench, SparkBench
  ○ *application benchmarks*: Linear Road, AIM Benchmark, Yahoo Streaming Benchmark, RIoT Bench

→ none of the above benchmarks integrates an *end-to-end real-world scenario* implementing a Big Data architecture integrating storage, batch and stream processing components
Our Requirements

- Create **configurable** data stream to simulate multiple scenarios:
  - real-time monitoring and dashboards (refresh rate in **less than 3 seconds**)
  - streaming hours of **history data for batch processing**

- Create **deterministic** data stream to:
  - **compare accurately** systems under test
  - **validate and verify** the workload results

- **Isolate the stream engine execution** as much as possible to avoid any external influence/bottlenecks, for example by the stream generation.

- **Preserve** the current BigBench specification, architecture, workload execution and metric.
Streaming Methodology (I)

- **Web-logs** are key-value pairs representing user clicks (**JSON file**), for example:

```
{"wl_id":845, "wl_webpage_name":"webpage#20", "wl_item_id":758, "wl_timestamp":"2013-01-01 01:17:37", "wl_key_1":"value_1", "wl_key_2":"value_2", ..., "wl_key_100":"value_100"}
```

- **Web-sales** example:

```
2013-01-27 16:12:32
```

- Web-logs and web-sales are generated in session window manner.

- Sort the entries according to the event timestamp and create data windows depending on the simulated scenario.
Streaming Methodology (II)

- Support for two window types:
  - Fixed Window
  - Sliding (Hopping) Window ($x = 2^y$)

- Configurable window parameters:
  - window size ($x$)
  - window slide ($y$) (e.g., hourly windows, starting every 30 minutes)
  - total runtime
Design Overview

- Adding 3 new components:
  - Stream Generator
  - Fast-access Layer
  - Stream Processing

- Support for 2 stream execution modes:
  - Active Mode - simulate real-time data streaming (in second ranges)
  - Passive Mode - simulate data ingestion and transformation on micro-batch processing (in hour ranges)
Active and Passive Streaming Modes

- Active mode: *parallel execution of the data stream generation and the actual stream processing.*

- Passive mode: *sequential execution of data stream generation and the actual stream processing.*
Workloads

- The streaming workload consists of five queries executed periodically on a stream of data (web-logs and web-sales), covering simple aggregation and pattern detection operations:
  
  - $Q_{S1}$: Find the 10 most browsed products in the last 120 seconds.
  
  - $Q_{S2}$: Find the 5 most browsed products that are not purchased across all users (or specific user) in the last 120 seconds.
  
  - $Q_{S3}$: Find the top ten pages visited by all users (or specific user) in the last 120 seconds.
  
  - $Q_{S4}$: Show the number of unique visitors in the last 120 seconds.
  
  - $Q_{S5}$: Show the sold products (of a certain type or category) in the last 120 seconds.
Metrics & Result Validation

- **Execution time** is the time between start and end of the query execution against the streaming data.

- **End-to-end streaming execution time** (Latency) - starting from the Stream Generator and stopping at the point where the data result is produced.

- Result validation based on scale factor similar to current BigBench validation (SF1):
  1. **Store persistently** the results of every query execution over a streaming window.
  2. **Compare** the results against the golden result once the benchmark run is finished.
Proof of Concept Implementation

Active Mode Components:
- Stream Generator in **Spark**
- Persistent Storage Layer in **HDFS**
- Fast-access Layer in **Kafka**
- Stream Processing in **Spark Streaming**

Passive Mode Components:
- Stream Generator in **Spark**
- Persistent Storage Layer in **HDFS**
- Fast-access Layer as **In-memory Buffer**
- Stream Processing in **Spark Streaming**
Conclusion

- We present a **stream processing extension** of the BigBench benchmark.

- Our approach proposes **configurable active and passive streaming modes** in order to cover the different streaming requirements (ranging from seconds to hours).

- It supports **fixed and sliding window streaming** to better address the common data streaming use cases.

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<th>Features</th>
<th>Active Mode</th>
<th>Passive Mode</th>
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Next Steps

- New implementation on Spark Structured Streaming replacing Spark Streaming.
- Adding other engines such as Flink and Samza.
- Extending the coverage of the stream SQL operators (new workloads) including clustering, pattern detection and machine learning.
- Support for:
  - sliding windows in active mode
  - out-of-order record processing within and outside of a window
  - parallel query execution
- Validation experiments on a large-scale cluster with different active and passive mode architectures.
Thank you for your attention!

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www.databench.eu
References


Backup Slides
$Q_{s1}$ (HiveQL Q5 in BigBench V2)

Find the 10 most browsed products in the last 120 seconds.

```sql
SELECT wl_item_id, COUNT(wl_item_id) as cnt
FROM web_logs
WHERE wl_item_id IS NOT NULL
GROUP BY wl_item_id
ORDER BY cnt DESC LIMIT 10;
```
Find the 5 most browsed products that are not purchased across all users (or specific user) in the last 120 seconds.

```sql
SELECT wl_item_id AS br_id, COUNT(wl_item_id) AS br_count
FROM web_logs
WHERE wl_item_id IS NOT NULL
GROUP BY wl_item_id;
view_browsed.createOrReplaceTempView("browsed");

SELECT ws_product_id AS pu_id
FROM web_logs
WHERE ws_product_id IS NOT NULL
GROUP BY ws_product_id;
view_purchased.createOrReplaceTempView("purchased");

SELECT br_id, COUNT(br_id)
FROM browsed LEFT JOIN purchased ON browsed.br_id = purchased.pu_id
WHERE purchased.pu_id IS NULL
GROUP BY browsed.br_id LIMIT 5;
```
Q_{S3} (HiveQL Q16 in BigBench V2)

Find the top ten pages visited by all users (or specific user) in the last 120 seconds.

```sql
SELECT wl_webpage_name, COUNT(wl_webpage_name) AS cnt
FROM web_logs
WHERE wl_webpage_name IS NOT NULL
GROUP BY wl_webpage_name
ORDER BY cnt DESC LIMIT 10;
```
Q_{s4} (HiveQL Q22 in BigBench V2)

Show the number of unique visitors in the last 120 seconds.

```sql
SELECT COUNT(DISTINCT wl_customer_id) AS uniqueVisitors
FROM web_logs
WHERE wl_customer_id IS NOT NULL
ORDER BY uniqueVisitors DESC LIMIT 10;
```
Q_{s5}  HiveQL

Show the sold products (of a certain type or category) in the last 120 seconds.

```sql
SELECT ws_product_id, COUNT(ws_product_id)
FROM web_sales
WHERE ws_product_id IS NOT NULL
GROUP BY ws_product_id
ORDER BY COUNT(ws_product_id) DESC LIMIT 10;
```